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Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network

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Abstract: A data-driven Bayesian network (BN) is used to investigate the effect of human factors on maritime safety through maritime accident analysis. Its novelties consist of 1) manual collection and analysis of the primary data representing frequencies of risk factors directly derived from maritime accident reports, 2) incorporation of human factors into causational analysis with respect to different maritime accident types, and 3) modelling by a historical accident data-driven approach, to generate new insights on critical human factors contributing to different types of accidents. The modelling of the interdependency among the risk influencing factors is structured by Tree Augmented Network (TAN), and validated by both sensitivity analysis and past accident records. Our findings reveal that the critical risk factors for all accident types are ship age, ship operation, voyage segment, information, and vessel condition. More importantly, the findings also present the differentiation among the vital human factors against different types of accidents. Most probable explanation (MPE) is used to provide a specific scenario in which the beliefs are upheld, observing the most probable configuration. The work pioneers the analysis of various impacts of human factors on different maritime accident types. It helps provide specific recommendations for the prevention of a particular type of accidents involving human errors.

Keyword: Maritime accident, Maritime safety, Bayesian networks, Data-driven Bayesian, Human reliability analysis, Maritime risk

1. Introduction

Most shipping accidents (e.g. collisions, groundings, crash, fire and explosions) are characterised with a feature of low probability-high consequence. Catastrophic maritime accidents may cause huge loss of human lives, damage to the society and environment (Zhang and Thai, 2016). Analysing maritime accidents becomes one of the effective ways to reduce the risks of maritime transportation. Maritime administrations conduct accident investigation to learn how the systems fail and why accidents happen (Schroder-Hinrichs et al., 2011). It then simulates maritime administrations to review and revise regulations, standards and management. To mitigate the risk and improve the safety of maritime transportation, the International Maritime Organisation (IMO) introduced the Formal Safety Assessment (FSA) methodology for its applications to the rule-making process (IMO, 2002; IMO, 2013). According to the literature, the organisation, working condition, and navigational environment are the major driving forces to maritime accidents (García-Herrero et al., 2012).

Although modern ships are highly equipped with advanced technologies (*e.g.* navigation technology, onboard information, bridge resource management systems), human factors present a major contribution to accidents. There is no consensus on the statistical analysis of the causations leading to maritime accidents, due to the different perspectives on the analysis and use of various investigation approaches. However, human errors, technical failures, and mechanical failures are traditionally highlighted as the main root causes of accidents (Celik and Cebi, 2009a). The maritime sector initiated the studies on the contribution of human and organisational factors (HOFs) to maritime accidents from the occurrence of the capsizing of the Herald of Free Enterprise in 1987 (Transport, 1987). Since then, accident investigations pay more attention to human factors in maritime safety. It is widely accepted that the human element, accounting for 75%-96% of maritime casualties, plays an important role in accidents involving modern ships (Trucco et al., 2008a, Fan et al., 2018, Tzannatos, 2010). Human factors are often viewed as causes behind anything that goes improperly at sea.

Human factors are usually adopted as a concept that considers other relevant factors, including workplace conditions, physical and natural environment, procedures, technology, training, organisation, management, as well as seafarers (*i.e.* fatigue, task load, mental state, etc.) (Psarros, 2015). Several researchers have studied the contribution of human and organisational factors to ship accidents (Chauvin et al., 2013, Chen et al., 2013, Xi et al., 2017). The majority of accidents occurred due to one of or the combination of the following causes: poor crew competence, fatigue, lack of communication, lack of proper maintenance, lack of application of safety culture and protocols or other procedures, inadequate training, poor situation assessment, and stress (Vinagre-Ríos and Iglesias-Baniela, 2013, Fan et al., 2018). Generally, seafarers often face more accidents than the crews working onshore, as reported by Roberts and Hansen (2002). Also, there is a consideration that a system for the training and assessment of the non-technical skills (NTS) of co-operation, leadership and management skills, situation awareness and decision making, needs to be established in the maritime industry (Saeed et al., 2016). Thus, the effective control of these causes will help reduce the risk and improve safety at sea.

Risk analysis is an effective way of devising mitigation measures that prevent accidents. Among the studies on the risk analysis of maritime transportation, historical data analyses have been widely used. A number of papers have used historical accident data for such purposes (Zhang et al., 2013; Zhang et al., 2016). Ronza et al. (2003) investigated 828 accidents in port areas using event trees to predict the frequency of accidents. Kujala et al. (2009) included detailed accident statistics over a ten-year period in a collision model, to analyse the safety in the Gulf of Finland. Jin and Thunberg (2005) proposed the logic regression model based on accident data from 1981-2000, to analyse fishing vessel accidents.

This study investigates how human factors combined with non-human factors affect maritime transportation using risk analysis. Allowing for the drawbacks arising from traditional studies, this study proposes a novel risk assessment of the human factors contributing to maritime accidents. Since 75-96% of maritime accidents involve human elements, it is worth of clarify the extent to which a maritime accident can be defined as a human-related maritime accident. This study aims at investigating how different risk factors generate, in an individual or combined manner, an impact on different types of human-related maritime accidents. Based on recorded maritime accident reports from the Marine Accident Investigation Branch (MAIB) and the Transportation Safety Board of Canada (TSB) between 2012 and 2017, a primary database is developed. Owing to the use of accident data, the Tree Augmented Network (TAN) model is developed to construct a BN and train the data, to propose a data-driven BN-based approach for accident analysis.

The rest of the paper is structured as follows. The literature review on human factors research in maritime accidents and data-driven BN-based maritime accident modelling is conducted in Section 2. Section 3 demonstrates the methodology of Risk Influencing Factors (RIFs) identification, BN structure learning, and sensitivity analysis. Section 4 analyses the results of the RIFs for different ‘accident types’, illustrates the combined manners generated by RIFs, and highlights the implications through providing a plausible explanation for the observed findings. Finally, Section 5 concludes the paper.

2. Literature review

2.1 Human factors in maritime safety studies

Since the United States Coast Guard (USCG) reported in 1993 that human factors had essentially caused approximately 80% of maritime accidents and near misses, there has been an overwhelming understanding that human factors play a significant role in a considerable number of incidents or catastrophes by triggering chain events. Also Branch et al. (2004) disclosed that watchkeeping manning levels and individual's abilities to discharge duties were essential factors resulting in collisions and groundings.

The preliminary findings of literature review are summarised in Table 1. For organisational factors, Lu and Tsai (2008) studied the influence of the safety culture in ship accidents, concluding that the job safety, management safety practices and safety training were among the top influencers. On the other hand, people surrendered the level of vessel safety standards to a profitable activity, due to commercial affairs (Vinagre-Ríos and Iglesias-Baniela, 2013). It showed that increase and decrease in the level of ship-owners' profits influence the amount of risk tolerated in their ship operation. From this point of view, human factors were also derived from the practices and operating policies established by shipping companies.

Table 1 Strengths and weaknesses of the relevant research

Researchers	**Journals**	**Strengths**	**Weaknesses**
Lu and Tsai, 2008	Accident Analysis & Prevention	Considered the organisational factors, and empirically evaluated the influence of safety climate on vessel accidents from a seafarer's perspective	Factors were limited and it did not illustrate the interaction between organizational factors.
Vinagre-Ríos and Iglesias-Baniela, 2013	The Journal of Navigation	Mentioned the increasing incidence of human errors, and pointed out how commercial affairs of shipping market influences the risk behaviour of shipping business decision-makers.	Not interacted with other risk factors
Antão and Guedes Soares, 2008	Reliability Engineering & System Safety	Identified the difference in the pattern of human factors and other factors associated with high-speed crafts accidents, as compared with the more traditional ocean-going ships	Human factors were limited to human tasks, including set speed, set heading, look out planning, trip maintenance, engine, and others.
Celik and Cebi, 2009	Accident Analysis & Prevention	Improved Human Factors Analysis and Classification System (HFACS) framework to identify the role of human factors in shipping accidents. Improvement of safety precautions in shipping companies	Did not reflect the influences between different factors levels.
Chen et al., 2013	Safety Science	The use of HFACS-MA model with WBA can help ensure the relevant latent conditions and indicate the adverse influences between different factors levels.	It needed a dedicated HOFs framework with detailed items specified for marine accidents and the weights of the HOFs identified.
Yang et al., 2013,	Ocean Engineering	Proposed a modified CREAM to facilitate human reliability quantification in marine engineering; developed a quantitative human reliability analysis method using fuzzy Bayesian; realised real time monitoring of marine engineers' failures under uncertainty	It required appropriate consideration of the influence of the CPCs with neutral effects in the establishment of belief fuzzy rule bases.
Soner et al., 2015	Safety Science	Used Fuzzy Cognitive Mapping (FCM) with HFACS to propose a novel proactive modelling and add value to predicting the root causes revealed in various levels.	Detailed predictions of suggested safety mechanisms need to be studied in order to manage the operational level.
Pristrom et al., 2016	Reliability Engineering & System Safety	Used data collected from the Global Integrated Shipping Information System (GISIS) together with expert judgement	There was no detailed human factors data.
Zhang et al., 2016	Safety Science	A literature review on expert knowledge and BN modelling for shipping accidents in view of risk and uncertainty.	New methods for experts' knowledge elicitation should be developed to improve the model validity.

Chauvin et al., 2013	Accident Analysis & Prevention	Used HFACS to identify contributory factors involved in 39 collisions; used MCA and hierarchical clustering to reveal three patterns of factors	The small number of collisions studied but the high number of variables.
Wang and Yang, 2018	Reliability Engineering & System Safety	Showed the key factors influencing waterway safety including the type and location of the accident and conducted a novel scenario analysis to predict accident severity.	The completeness of the data mined from the text case was arguable. It focused more on objective variables than human factors.

However, human factors have complex casual relations with each other. Lema et al. (2014) applied a K-means clustering method to indicate that human factors coexist with the condition of a ship and other external factors. It was widely accepted that human factors were associated with a variety of unsafe actions, behaviours, omissions and hazardous conditions, and the human element was a key factor in maritime accidents (Antão and Guedes Soares, 2008). A lot of attention has been paid to the risk analysis of accidents' causes related to human factors. Celik and Cebi (2009b) proposed a Human Factors Analysis and Classification System (HFACS) approach to identify human factors in shipping accidents. It revealed the hierarchy structure of human factors and the logic relations within the structure. In line with HFACS, Reason's Swiss Cheese Model and Hawkins' SHEL model, Chen et al. (2013) modified the HFACS to make it more applicable to maritime accidents (*i.e.* HFACS-MA model), to comprehensively describe HOFs in maritime sector. In addition, human performance defined by human reliability in accidents was analysed, and the human failure probabilities were estimated to assess the risk level of shipping industry (Yang et al., 2013, Yoshimura et al., 2015, Yang and Wang, 2012). Soner et al. (2015) combined Fuzzy Cognitive Mapping (FCM) with HFACS to generate a proactive model in fire prevention on-board ships, which revealed that human factors were significant, leading to the failures of maritime operations with an enormous and long-term loss.

To analyse human factors, the maritime accident database is used as one of the most valuable sources to obtain the primary data, including the global database like Global Integrated Shipping Information System (GISIS) (Pristrom et al., 2016), and the historical accident data collected from national/regional maritime administration (Zhang et al., 2016). However, such databases contain less detailed information than the extractions from maritime accident reports. From this perspective, the investigation reports of maritime accidents provide the navigational circumstance, process of the failure chain, environmental information, direct or indirect causes of the accidents, and the actions taken during the accidents. Even the hidden potential hazards and causal relations between various factors are demonstrated in detail. However, few studies utilised accident reports to conduct accident and human factors analysis due to the time-consuming process of extracting the data from each report. Therefore, even studies utilising accident reports provided limited content of the data sources. For instance, Chauvin et al. (2013) underlined 39 vessels involved in 27 collisions derived from the accident reports, identifying the importance of Bridge Resource Management (BRM) for situations of navigation in restricted waters. Chen et al. (2013) utilised the accident reports of selected cases from MAIB for accidents analysis providing a complement measure. Wang and Yang (2018) analysed all accident investigation reports by China's Maritime Safety Administration (MSA), to conclude the key risk factors influencing waterway accident severity.

To determine human factors in maritime, 109 accident reports extracted from 152 reports in MAIB and 52 accident reports obtained from 61 reports in TSB during 2012-2017 have been reviewed, as these two organisation are among the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015). According to such reports, human factors are derived.

Previous studies relying mainly on the secondary database for RIFs identification were unable to present primary information from accident reports. One of the novelties of this study is to incorporate human factors derived from accident reports into accident analysis, combined with other external factors, considering both subjective and objective factors. New insights brought by the data acquisition through the investigation of accident reports, cannot be achieved by only relying on the secondary or existing databases.

2.2 Data-driven BN in maritime accident modelling

Quantitative risk and reliability analysis techniques have been widely used to reduce the probability of failure in maritime sectors, including Hazard and Operability Studies (HAZOP), Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Bayesian Network (BN). (Yeo et al., 2016; Zhang and Thai, 2016). BN has become popular for maritime risk modelling during the period of 2004–2013. It has been widely applied to maritime risk analysis, including collision risk assessment (Hanninen and Kujala (2012); Ma et al., 2016), human reliability analysis (Martins and Maturana, 2013), and risk estimation (Montewka et al., 2014). Zhang et al. (2013) and Zhang et al. (2014) estimated the navigational risk through FSA and BN to improve the navigational safety in the Yangtze River, and established the BN for the analysis and prediction of the congestion risk of inland waterways. In addition, BN was constructed to represent the dependencies between the indicators and accident consequences (Zhang et al., 2016), revealing that the accident consequences were the most sensitive to the position where the accidents occurred.

Weber et al. (2012) pointed out that the number of publications on BN in risk analysis increased every year, due to its advantages of learning and inference algorithms. Compared with other classical methods used in dependability analysis, BN sustains its advantages by conducting multi-state variable modelling. For example, BN displays similar features as the Fault Tree (FT) which fits for the two-state variables, but has additional ability to model a multi-state variable and several outputs. In addition, FT can also be translated into BN to make it applicable for the system (Khakzad et al., 2011, Mahadevan et al., 2001, Bobbio et al., 2001, Trucco et al., 2008b, Montani et al., 2006). However, the system modelling tends to be complicated with increasing variables, while leading to an apparent increase of parameters and related functions (Weber et al., 2012). For instance, Markov chain (MC) analyses the probability of a failure event with the dependencies among variables and has the ability to represent multi-state variables, which implies sophisticated system when the number of variables increases. However, BN has required a relatively low number of parameters and a small-size conditional probability table.

Moreover, BN is a competitive approach for maritime risk modelling owing to its abilities to utilise either expert knowledge and/or data-driven methods. When failure data in the relevant investigations are absent, expert knowledge continues to be an essential data source for shipping accident modelling (Fu et al., 2016; Zhang and Thai, 2016). Experts' knowledge was found to play an essential role in BN structures, regarding the definition of the relative probabilities due to the insufficient historical data (Hänninen and Kujala, 2014; Zhang and Thai, 2016).

In light of this characteristic, BN is appropriate for modelling maritime accidents since it enables quantitative risk analysis of HOFs (Trucco et al., 2008b, Akhtar and Utne, 2014, Castaldo et al., 2016) and allows for analysing RIFs to rationalise relevant regulations for risk control practice by a data-driven approach (Yang et al., 2018). However, compared to the studies using expert judgements in BN construction, data-driven BN in maritime risk analysis involves less subjective bias but is scarce, requiring more experimental evidence to be collected before its wide practical applications.

To fulfil this gap, the study uses new primary data derived from maritime accident reports to conduct a data-driven BN to generate the structure of RIFs. Consequently, it will provide new insights on the differentiation among critical human factors contributing to each of the different types of maritime accidents.

3. Methodology

3.1 Identification of RIFs

To analyse the maritime accident types under various RIFs, identifying and selecting the RIFs from the accident reports are necessary. The data was obtained from case-by-case analysis of recorded maritime accidents from MAIB, and TSB. These reports are among the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015).

To generate the RIFs, the procedure consists of four stages: (1) online database searching, (2) reports screening and selection, (3) refining and analysis, (4) RIFs selection. Through online database searching, the maritime accident reports from MAIB (https://www.gov.uk/maib-reports) and TSB (http://www.bst-tsb.gc.ca/eng/rapports-reports/marine/index.html) between Jan. 2012 to Dec. 2017 were obtained. In order to ensure the human element relevance, these accident reports are screened with a focus on human factors-related accidents. For instance, some accidents disobeying rules of passengers or weather caused accidents in small fishing vessels, are discarded due to that they are irrelevant to human factors. Therefore, the study generates the database with 161 reports involving 208 vessels. Then, the reports are further refined and analysed, especially according to the illustration of 'safety issues' and 'common factors'. To identify the most relevant factors (i.e. 32 risk factors in Table 2), manual analysis from original maritime accident reports generates 77 factors first. All the risk factors relating to human performance were first identified from maritime accident reports. Domain experts were then invited to fine turn them to merge those of high similarity. The other factors are retained even they have revealed some interdependence, but in the meantime present significant difference. The quantitative extent to which one factor influences another is calculated through the TAN modelling.

Moreover, it is necessary to set the appropriate criterion to select RIFs. Using a low criterion threshold allows more human-related RIFs to be selected. However, involving a large number of variables with a low sample size will not be able to ensure the robustness of the model. Oppositely, using a high criterion threshold offers sufficient samples for risk analysis, but excludes some important human-related factors, such as factors 27, 13, 30. So the criterion threshold of 19.35% was calculated from averaging the frequencies of all common factors in Table 2. Therefore, 14 common factors whose frequencies were higher than the average value, 19.35%, were extracted as RIFs in the study. They are sea condition, information, management system, weather condition, equipment and device, clear order, supervision and supports, experienced, communication, vessel condition, risk assessment, safety culture, complacent, regulation.

Table 2 The risk factors contributing to human errors in maritime accidents.

Number	Risk factors	Frequency
1	Poor communication and coordination	30.77%
2	Ineffective supervision and supports (lone watchkeeper or working isolated, improper supervision of loading operation)	32.69%
3	No detailed passage plan or revised passage plan was unsafe	13.46%
4	Swift duty between pilots and seafarers or change of the steering mode	1.44%
5	Over-reliance on devices (AIS, GPS…), or poor lookout	15.38%
6	Fast speed	9.62%

7	No clear order (not accurately interpret and apply the requirements of a safe manning document)	37.50%
8	Limited time to respond	12.50%
9	Lack of situation awareness	14.42%
10	Fatigue/asleep/tiredness and desire to rest	13.46%
11	Emotion (low level of arousal, panic, anger, unhappiness)	1.92%
12	Unfamiliar with/lack of equipment knowledge, inexperienced, ill-prepared	32.69%
13	Complacent about the duties or underestimation of the severity of the condition (low state of alertness)	21.63%
14	Recreation drugs, alcohol	6.73%
15	Cognitively overload	4.81%
16	Physical incapacitation	0.96%
17	Distracted/insufficient attention	16.35%
18	Stress	0.48%
19	Poor condition of the vessel, increasing complexity of propulsion arrangements, and modifications made to vessels, size	28.85%
20	Devices and equipment on board not fully utilized or operated correctly (BNWAS switched off, alarm system not in the recommended position or not noticed)	37.98%
21	Ergonomic impact of innovative bridge design (visual blind sector ahead, motion illusion)	11.06%
22	Insufficient or lack of updated information (poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment); no automatic means or without indicators for necessary observing (working indicators, light)	45.67%
23	Weather condition: wind, visibility (dense fog)	39.42%
24	Sea condition: falling tide, current, waves	53.37%
25	Noisy and vibrating environment	0.96%
26	Fairway traffic (traffic density, repetitive nature of the route)	16.35%
27	Inappropriate or ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	19.71%
28	Lack of risk assessment	26.92%
29	Dysfunctional management system (shore management, maintenance management, bridge source management, on board management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	40.87%
30	Lack of safety culture, precautionary thought	24.52%
31	No medical and fitness standards for crews	2.40%
32	Commercial pressure, public pressure or industrial pressure (financial constrains)	4.33%

However, human factors in maritime accidents are usually combined with other external factors, such as sea condition, weather condition, fairway traffic, and vessel condition, to affect the safety procedure in navigation. From this perspective, it is beneficial to combine human factors with other non-human RIFs to investigate their combined effect on maritime safety. Referring to the previous factors analysis studies (Wang and Yang, 2018; Fan et al., 2020), 16 important risk factors are described as important factors contributing to maritime accidents as stated in the literature and accident reports. It contains ship type, hull type, ship age, length, gross tonnage, ship operation, voyage segment, ship speed, vessel condition, equipment/device, ergonomic design, information, weather condition, sea condition, time of day, fairway traffic. It is evident that five overlapped factors exist in both groups (i.e. human and non-human), including vessel condition, equipment/device, information, weather condition, sea condition. These factors not only make significant contributions to maritime accidents but also are connected to human factors in maritime safety. At last, it encompasses a total of 25 RIFs, seen in Table 3.

Table 3 25 RIFs defined in maritime accidents

No	**RIFs**	**Notation**	**Description**	**Corresponding values**
1	Ship type	R_{ST}	Passenger vessel, tug, barge, fishing vessel, container ship, bulk carrier, RORO, tanker or chemical ship, cargo ship, others.	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
2	Hull type	R_{HT}	Steel, wood, aluminium, others	1, 2, 4, 5
3	Ship age (years)	R_{SA}	(0 5], [6 10], [11 15], [16 20], >20, NA	1, 2, 3, 4, 5, 6
4	Length (m)	R_L	≤100, >100, NA	1, 2, 3
5	Gross tonnage (GT)	R_{GT}	≤300, 300 to 10000, >10000, NA	1, 2, 3, 4
6	Ship operation	R_{SO}	Towing, Loading/unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, others	1, 2, 3, 4, 5, 6, 7, 8
7	Voyage segment	R_{VS}	In port, Departure, Arrival, Mid-water, Transit, others	1, 2, 3, 4, 5, 6
8	Ship speed	R_{SS}	Normal, fast	1(normal), 2(fast)
9	Vessel condition	R_{vc}	The condition of vessel has nothing to do with the accidents; Increasing complexity of propulsion arrangements, modification made to vessels, size contributes to the accidents	1(good), 2(bad)
10	Equipment /device	R_E	Devices and equipment on board operate correctly; Devices and equipment not fully utilised or operated correctly (*e.g.*, BNWAS switched off, alarm system not in the recommended position or not noticed)	1(good), 2(bad)
11	Ergonomic design	R_{ED}	Ergonomic friendly or ergonomic aspects has nothing to do with accidents; Ergonomic impact of innovative bridge design (*e.g.*, visual blind sector ahead, motion illusion)	1(good), 2(bad)
12	Information	R_I	Effective and updated information provided; Insufficient or lack of updated information (*e.g.*, poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment, without working indicators or light for necessary observing)	1(good), 2(bad)
13	Weather condition	R_{WC}	Good/poor considering rain, wind, fog, visibility	1(good), 2(bad)
14	Sea condition	R_{SC}	Good/poor considering falling/rising tide, current, waves	1(good), 2(bad)
15	Time of day	R_{TD}	07:00 to 19:00, other	1(good), 2(bad)
16	Fairway traffic	R_{FT}	Good or poor considering complex geographic environment, dense traffic, or receptive nature of the route contributing to ignorance	1(good), 2(bad)
17	Communication	*A1*	Good or poor communication and coordination	1(good), 2(bad)
18	Supervision	*A2*	Effective or ineffective supervision and supports (lone watchkeeper or working isolated, improper supervision of loading operation)	1(good), 2(bad)
19	Clear order	*A6*	Good or unclear order from documents (not accurately interpret and apply the requirements of a safe manning document)	1(good), 2(bad)

20	Experienced	*A11*	Familiar or unfamiliar with/lack of equipment knowledge, experienced or inexperienced, good or ill-prepared;	1(good), 2(bad)
21	Complacent	*A12*	Properly understand or complacent about the duties/underestimation of the severity of the condition (low state of alertness)	1(good), 2(bad)
22	Regulation	*A18*	Good or inappropriate/ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	1(good), 2(bad)
23	Risk assessment	*A19*	Good or lack of risk assessment	1(good), 2(bad)
24	Management	*A20*	Good or dysfunctional management system (including shore management, maintenance management, bridge source management, on board management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	1(good), 2(bad)
25	Safety culture	*A21*	Good or lack of safety culture, precautionary thought	1(good), 2(bad)

Most of the definitions of variables' states can be extracted from accident investigation reports. For example, 'accident type', 'ship type', 'hull type', 'ship operation', and 'voyage segment', are classified into different states according to the classification of MAIB or TSB, which are widely accepted in the industry. In the process of accident reporting analysis, hull type are defined as steel (1), wood (2), glass reinforced plastic (3) (MAIB 8-2017), aluminium (4), foam reinforced plastic (5) (MAIB 7-2017), polyester (6) (MAIB 24-2016). However, the accident statistics reveals that 3, 5, and 6 take account a very low proportion in total. Therefore, these three types are combined as one – 'others' and defined as state 5. Finally, in the table, it is presented as state 1,2,4,and 5. The other variables are graded according to the literature (e.g. Wang and Yang, 2018), including 'ship age', 'length', and 'gross tonnage'. In addition, 'vessel condition', 'communication', 'supervision', etcetera, are graded based on whether it is blamed for the faults in accidents, as data characteristic described in the reports.

3.2 BN structuring learning- TAN

Using the RIFs, there are two approaches for the BN structure learning. One relies on expert knowledge, which takes advantage of subjective causal relationships to build a BN structure. An alternative approach is a data-driven method to reveal the interactive dependencies between RIFs, which relies on the learning algorithm and data correlation in the BN model. This study develops the BN structure by the latter approach. First, the raw data from maritime accident reports is manually analysed to generate a database containing 161 reports involving 208 vessels. The sample size for such database is applicable for the risk analysis using a data-driven approach. As far as data-driven approach is concerned, there are many approaches, *e.g.* Naïve Bayesian Networks (NBN), Augmented naive Bayesian Networks (ABN), and TAN. Among them, TAN learning constructs qualitative BN representing RIFs' interactive dependencies, which helps generate insights on critical human factors contributing to different types of accidents. In addition, Friedman et al. (1997) pointed out that TAN outperforms naive Bayes, while maintaining the computational simplicity and robustness that characterise naive Bayes. TAN is proved to be more competitive and accurate than other data-driven network construction approaches (Murphy and Aha, 1996).

A BN encodes a joint probability distribution over a set of random variables *U*, which is an annotated directed acyclic graph (DAG). Let $U=\{A_1,\dots A_n, C\}$ where *n* stands for the number of RIFs, the variables $A_1,\dots A_n$ are the RIFs and *C* is the class variable (accident types). Consider a graph structure where the class variable is the root, that is, $\prod C=\varnothing$ ($\prod C$ denotes the set of parents of *C* in *U*), and each RIF has the class variable as its unique parent, *i.e.* $\prod A_i=\{C\}$ for $1\le i\le n$. A BN defines a unique joint probability distribution over *U* given by

$$P(A_1,\dots A_n, C)=P(C)\cdot\prod_{i=1}^{n}P(A_i\mid C)\,. \tag{1}$$

The DAG on $\{A_1,\dots A_n\}$ is a tree if $\prod A_i$ contains only one parent for all A_i, except for one variable without parents (referred as the root). There is a function π which can define a tree over $A_1,\dots A_n$, if there is exactly one *i* such that $\pi(i)=0$ (*i.e.* the root of the tree), and there is no sequence $i_1,\dots i_k$ such that $\pi(ij)=i_{j+1}$ for $i\le j<k$ and $\pi(i_k)=i_1$ (*i.e.*, no cycles). Such a function defines a tree network where $\prod A_i=\{C,\dots A_{\pi(i)}\}$ if $\pi(i)>0$, and $\prod A_i=\{C\}$ if $\pi(i)=0$.

Learning a TAN structure is an optimisation problem. Solving this problem follows the general procedure proposed by Chow and Liu (1968), who used conditional mutual information between attributes. The function can be defined as

$$I_P(A_1,A_j\mid C)=\sum_{a_{ii},a_{ji},c_i}P(a_{ii},a_{ji},c_i)\log\frac{P(a_{ii},a_{ji}\mid c_i)}{P(a_{ii}\mid c_i)P(a_{ji}\mid c_i)} \tag{2}$$

where I_P represents the conditional mutual information, a_{ii} is the i^{th} state of RIF A_i, a_{ji} is the i^{th} state of RIF A_j, c_i is the i^{th} state of 'accident type'. The optimisation problem, *i.e.* learning a TAN structure, is to find a tree defining function π over $A_1,\dots A_n$ such that the log likelihood is maximised.

3.3 Sensitivity analysis and model validation

3.3.1 Mutual information

The mutual information represents the dependence between two variables in the probabilistic theory (Yang et al., 2018). Deriving from the entropy theory, mutual information is described as an indicator showing the uncertainty of the dataset and interpreted as entropy reduction. The mutual information explains how strong the relationship between the RIF and 'accident type'.

One objective of this study is to identify the relationship between the relevant RIFs and a particular 'accident type'. 'Accident type' is first determined as the fixed variable in mutual information. In this way, the mutual information between the 'accident type' and the RIFs can be defined as follows:

$$I(s,\alpha_{\mathrm{i}}) =- \sum_{\mathrm{s},i} P(s,\alpha_{ij}) \log_b \frac{P(s,\alpha_{ij})}{P(s)P(\alpha_{\mathrm{ij}})} \qquad (1)$$

where S is 'accident type', α_{i} represents the ith RIF, α_{ij} represents the jth state of the ith RIF, $I(S,\alpha_{\mathrm{i}})$ is the mutual information between 'accident type' and the ith RIF. The larger the value of mutual information is, the stronger the relationship between α_{i} and 'accident type'. In this way, calculating the value of mutual information can eliminate the RIFs that are relatively less relevant to the 'accident type'. Then the remaining RIFs are extracted as significant variables with regards to a selected accident type in the model.

3.3.2 Sensitivity analysis

3.3.2.1 Joint probability

Another form of sensitivity analysis is based on a calculation of the network joint probability, which determines how the RIF influences 'accident type'. The value of the target node (*e.g.* 'accident type') is calculated when the state of RIFs is assigned with different values, and the states of the other variables are locked. The calculation of joint probability can be seen in (Wang and Yang, 2018; Trucco et al., 2008b).

For example, there are only two variables 'ship type' and 'ship operation', and 'ship type' is the parent node of 'ship operation', Set 'ship type' as M, 'ship operation' as N, '$M=M_i$' means the vessel is at its ith 'ship type' state, and the same goes to '$N=N_j$'. According to Baye's rules, the joint probability can be calculated as:

$P(M=M_i, N=N_j) = P(M=M_i) \times P(N=N_j | M=M_i)$, where $P(M=M_i, N=N_j)$ refers to the joint probability that events '$M=M_i$' and '$N=N_j$' both occur, $P(M=M_i)$ is the prior probability of the ith 'ship type', $P(N=N_j | M=M_i)$ denotes the conditional probability of the occurrence of ith 'ship type' state given that jth 'ship operation' state occurs.

3.3.2.2 True Risk Influence (TRI)

Once the RIFs are extracted from the mutual information calculation, there is another form of sensitivity analysis to determine the effects of different RIFs in a combined way, *e.g.* scenario simulation. The traditional way sets the scenario with all the other nodes (apart from the investigated ones) locked. Then the states of target node are updated gradually. It is applicable for variables with two states, but does not suit for variables with more than two states Alyami et al. 2019). In this case, the multi-state RIFs make the traditional scenario simulation inappropriate.

To overcome the disadvantage of the traditional scenario simulation, a new method was proposed by Alyami et al. (2019). This method aids to obtain the High Risk Inference (HRI) of a type of accidents (*e.g.* collision), by increasing the probability of the state producing the highest influence on collision to 100%. Then it helps calculate the Low Risk Inference (LRI) of collision by increasing the probability of the state generating the lowest influence on the collision to 100%. Then, calculating the average value of HRI and LRI concludes the True Risk Influence (TRI) of each RIF in the case of a particular accident type.

Subsequently, the similar analysis procedure is applied to other accident types, ‘grounding’ and ‘flooding’, etc., to obtain the variable influence on ‘accident type’. Therefore, the sensitivity analysis calculates the TRI values of variables in different accident types, which illustrates the RIFs’ influences on accident types. In this way, the average TRI values of all accident types ranks the variables’ effects on the ‘accident type’. The higher a TRI value is, the higher its corresponding RIF’s effect on ‘accident type’.

3.3.3 Model validation

Two axioms to be satisfied in the sensitivity analysis (Yang et al., 2009, Zhang et al., 2013) are expressed as below:

Axiom 1: A slight increase or decrease in the prior probabilities of each RIF, should contribute to the correspondence increase or decrease in the posterior probability of the target node (*i.e.* accident type).

Axiom 2: The total influence of the integration of the probability variations of x parameters should be no smaller than the one from the set of y ($y \in x$) RIFs.

Moreover, the validity of the proposed BN model is also conducted by simulating the past maritime accidents with the associated parameter settings to test if the model can deliver the result reflecting the reality.

3.4 Scenario analysis

BN modelling can also explain the most probable scenario with reference to a particular accident type. Providing a plausible explanation for the observed findings is called the most probable explanation (MPE). It is a special case of the maximum a-posteriori probability. In case that results of regular belief updating are questionable, the MPE can be used to identify the states of RIFs to provide a scenario for which the beliefs are upheld. It finds a completely specified scenario easier to understand. Then the study gains insights by putting the BN in an MPE mode, entering the evidence, and observing the most probable configuration for the investigated maritime accident type.

4. Results and discussion

4.1 Description of accident types

To generate the RIFs in maritime accidents according to the procedure in Section 3.1, a case-by-case analysis is conducted. In this way, 25 RIFs are defined as the variables in Table 3 for the BN construction. In the quantitative analysis of BN modelling, the accident type is defined as a dependent variable, classified into collision, grounding, flooding fire/explosion, capsize, contact/crush, sinking, overboard, and others, as presented in Table 4. These accident types are defined with respect to the classification of MAIB's maritime accident reports.

Table 4 Accident type

No.	**Accident type**
S1	Collision
S2	Grounding
S3	Flooding
S4	Fire/explosion
S5	Capsize
S6	Contact/crush
S7	Sinking
S8	Overboard
S9	Others

4.2 TAN modelling

To generate the BN model, 25 RIFs are involved to demonstrate their relationships with the dependent variable (*i.e.* accident type). The Netica software package (Norsys, http://www.norsys.com) is applied to assist the calculation. It has a 'learning network' function that develops the TAN network based on Eq. (2). The structure of BN is presented in Fig. 1. After the BN qualitative structure is trained by the data, it is carefully checked by domain experts to ensure all the links between the nodes are meaningful. In this study, no changes are made in the fine-tune process since all the interrelationship suggested by the data reflect the reality.

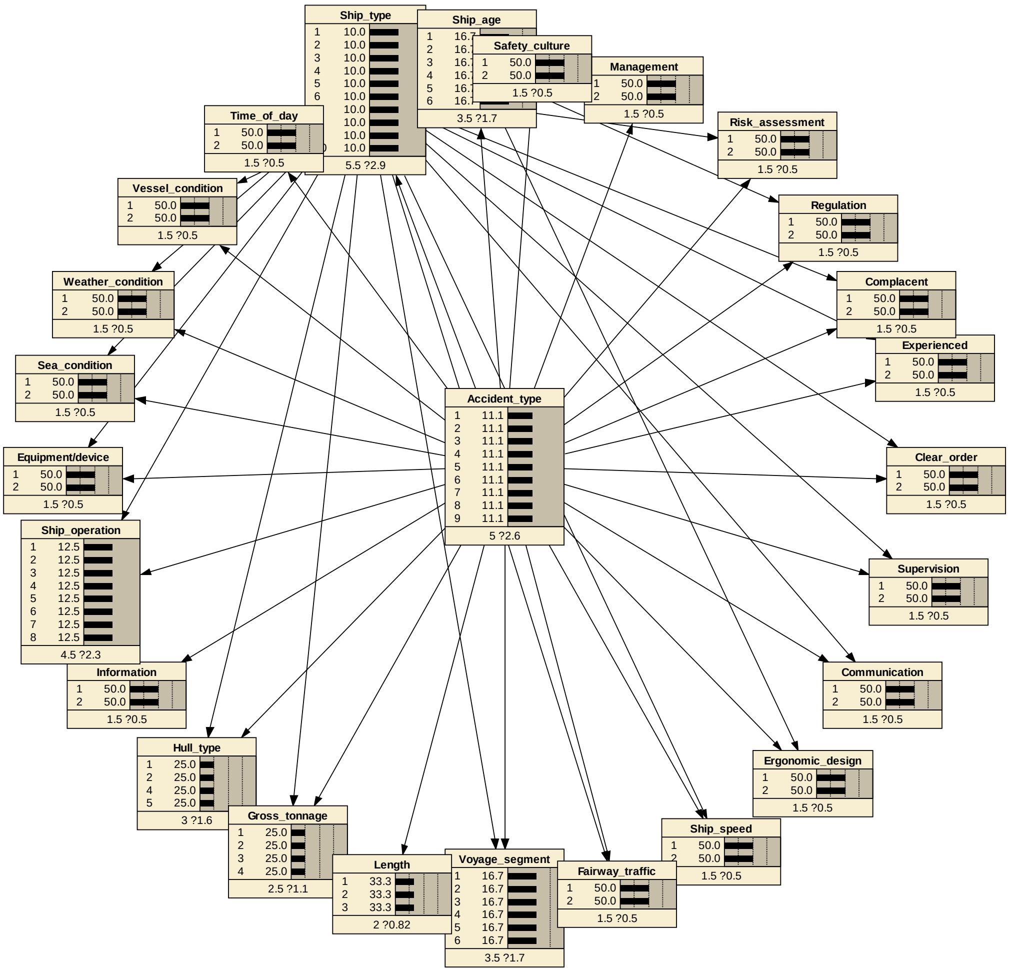

Fig. 1. Proposed BN for analysis of accident types probability

Based on the TAN model, the parameter learning of CPTs from the cases is conducted by Netica Software using the counting-learning algorithm (https://www.norsys.com/WebHelp/NETICA/X_Counting_Learning_Algorithm.htm). Once the CPTs are constructed and obtained, the posterior probabilities of each variable can be calculated. The statistical analysis of the probability of variables, reveals interesting initial findings for useful insights regarding safety caution and accident prevention as follows.

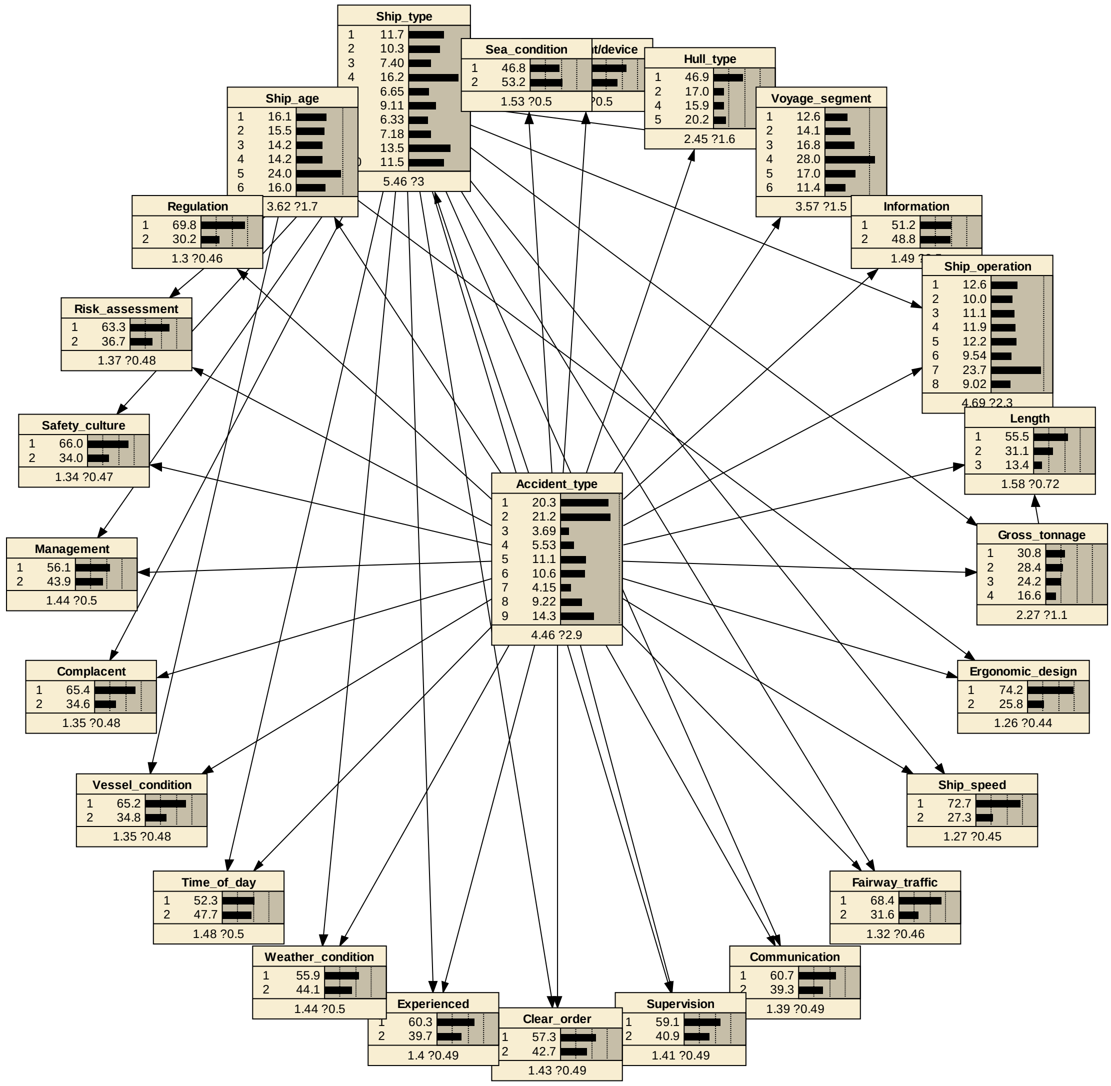

Fig. 2. Results of TAN

Fig. 2 presents the results of TAN involving all the retained 25 RIFs. Among the accidents, grounding and collision are among the most frequent accident types, accounting for 20.3% and 21.2%, respectively.

4.3 Sensitivity analysis

4.3.1 Mutual information

The mutual information between “accident type” and RIFs is demonstrated in Table 5. From this point of view, the variables with higher $I(s,R_k)$ reflects essential impacts on “accident type”. When “accident type” is the parent node, “ship age” with the corresponding mutual information value of 0.05422, has the largest effect on the accident type. Meanwhile, it can be seen that many mutual information values are less than 0.03 in Table 5. 0.03 is selected in this study as the threshold for the selection of such factors for further discussion. Variables ‘ship age’, ‘ship operation’, ‘voyage segment’, ‘vessel condition’, ‘information’, are selected to be calculated for the factor analysis in the next step. However, it does not rule out the possibility of using a smaller value to take into account more factors in the discussion when and where appropriate. From a methodological perspective, the method of using mutual information can provide an effective way to analyse the influential individual RIFs in a prioritised list.

Table 5 Mutual information shared with ‘Accident type’

Node	**Variance Reduction**	**Percentage (%)**	**Mutual Info**	**Percentage (%)**	**Variance of Belief**
Ship_age	0.02399	0.284	0.05422	1.84	0.0015433
Ship_operation	0.3115	3.69	0.05132	1.74	0.0030026
Voyage_segment	0.11	1.3	0.03595	1.22	0.0013546
Vessel_condition	0.07391	0.874	0.03171	1.07	0.0006767
Information	0.06113	0.723	0.03042	1.03	0.0010573
Ship_type	0.03119	0.369	0.02891	0.98	0.0011112
Safety_culture	0.01585	0.188	0.02871	0.973	0.000501
Hull_type	0.1171	1.39	0.02838	0.962	0.0008351
Gross_tonnage	0.0414	0.49	0.02482	0.841	0.0010064
Regulation	0.01091	0.129	0.02306	0.782	0.0005812
Length	0.02874	0.34	0.02151	0.729	0.0003882
Ergonomic_design	0.07421	0.878	0.0194	0.657	0.0006816
Sea_condition	0.0168	0.199	0.01774	0.601	0.0006831
Risk_assessment	0.06751	0.799	0.01466	0.497	0.0004953
Experienced	0.000957	0.0113	0.01271	0.431	0.0003126
Ship_speed	0.006733	0.0797	0.01172	0.397	0.0003134
Weather_condition	0.004131	0.0489	0.00889	0.301	0.0004858
Management	0.02553	0.302	0.00851	0.288	0.0001854
Clear_order	0.01196	0.142	0.00707	0.24	0.0002377
Fairway_traffic	0.03498	0.414	0.00704	0.238	0.0001619
Time_of_day	0.04428	0.524	0.00671	0.227	0.0002614
Complacent	0.003327	0.0394	0.006	0.203	0.000211
Communication	5.57E-05	0.000659	0.00547	0.185	0.0000786
Equipment/device	0.003186	0.0377	0.00541	0.183	0.0001612
Supervision	0.01893	0.224	0.00399	0.135	0.0001467

4.3.2 Sensitivity analysis

With regard to the most important variables influencing each of the investigated accident types, the next step is to figure out how these variables (the states of variables) affect the target accident type. To do so, the calculation of a joint probability of each variable and ‘accident type’ is presented in Table 6.

Table 6 The joint probability of the TAN model

					Ship age				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	23.6	19.8	3.69	3.88	12	13.9	**2.56**	7.7	12.9
2	22.4	21.1	2.2	4.99	**8.81**	8.73	3.8	8.21	**19.7**
3	**14.8**	23.5	**7.24**	**8.87**	8.93	11.2	**7.74**	8.92	**8.82**
4	15.8	22.5	2.69	**3.72**	**13.7**	12.6	3.33	12.9	12.8
5	16.8	**27.7**	4.27	5.58	11.7	**7.02**	4.11	**7.15**	15.7
6	**29.3**	**6.95**	**2.07**	6.52	10.6	**14.3**	4.13	**13.2**	13

				Ship operation					
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	**12.8**	25.3	3.3	**4.74**	15.2	9.75	4.48	7.9	16.5
2	15.9	16.3	4.1	**6.5**	10.3	11.1	4.57	9.81	**21.4**
3	14.4	**28.4**	4.08	5.32	9.28	11.9	4.14	8.9	13.6
4	16.5	21.6	3.51	5.05	12.5	12.2	3.92	9.36	15.4
5	16.9	**14.2**	4.45	5.12	**15.4**	9.69	3.98	**15.9**	14.3
6	16.6	20	4.26	6.75	10.7	11.6	**5.26**	9.27	15.7
7	**35.7**	22.8	**2.64**	5.19	**6.51**	**8.71**	**3.14**	**6.08**	**9.23**
8	17.5	18	**4.51**	6.48	12.7	**12.2**	5.03	9.82	13.7
				Voyage segment					
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	15.3	**15.6**	4.24	6.03	**13.5**	11	4.72	9.95	**19.6**
2	20.3	23.5	3.73	5.31	12.6	10.6	4.16	7.96	11.8
3	**11.5**	**28.5**	3.2	5.44	**7.72**	**15.9**	4.29	7.54	15.9
4	25.4	22.1	**3.17**	5.34	11.3	**5.86**	**2.99**	10.6	13.3
5	**27.5**	17.7	3.89	**5.02**	10.9	9.84	4.67	**7.51**	**13**
6	16.5	16.9	**4.6**	**6.53**	11.1	14.2	**5.12**	**11.8**	13.3
				Vessel condition					
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	**24.3**	**21.191**	**3.63**	**4.46**	**9.56**	**11.5**	**2.22**	**10.1**	**13.1**
2	**12.8**	**21.212**	**3.8**	**7.53**	**13.9**	**8.99**	**7.76**	**7.52**	**16.5**
				Information					
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
1	**21.8**	**15.8**	**3.33**	**6.17**	**13.2**	**7.28**	**4.28**	**10.6**	**17.6**
2	**18.7**	**26.8**	**4.06**	**4.86**	**8.86**	**14.1**	**4.01**	**7.82**	**10.8**

According to Table 6, the state of each variable that poses the highest influence on an accident type is shown (in bold value), as well as the state of each variable that poses the lowest influence on an accident type (in bold value). For example, when a ship is in the state of ‘on passage’, there is the highest probability for the accident to be ‘collision’ (35.7%); when ‘ship operation’ is the state of ‘towing’, there is the lowest probability to be ‘collision’ (12.8%). However, when a ship is in ‘pilotage’, there is the highest probability to be ‘grounding’ (28.4%); in ‘fishing’ operation, there is the lowest probability to be ‘grounding’ (14.2%). For the voyage segment, when in the state of ‘transit’, a ship has the highest probability to be in ‘collision’ (27.5%); when in ‘arrival’ segment, it has the lowest probability to be in ‘collision’ (11.5%), but has the highest probability to be in ‘grounding’ (28.5%). As far as the ship age is concerned, a ship with ages from 11 to 15 has the lowest probability to be involved in ‘collision’ (14.8%), whereas a more than 20-year-old ship has the highest probability to be involved in ‘grounding’(27.7%). Despite good vessel condition and the condition of good information, a ship can still highly associate with ‘collision’, whereas the situation of poor information on-board ship exposes the highest risk of ‘grounding’.

In this way, it demonstrates the influence of certain state of a single variable on an accident type. Moreover, it illustrates how different states of single variable contributes to the probability of a particular accident type. Generally, more attention should be paid to the red highlighted with the state of the single variable under an accident type, as these situations show high probabilities of accidents.

In terms of TRI sensitivity analysis, Table 7 demonstrates the TRI value of ‘ship age’ against collision. Table 8 indicates the values of all RIFs for all accidents. Moreover, by comparing the updated value of the target node, it is claimed that the model is in line with Axiom 1.

Table 7 TRI of a risk variable (ship operation) for collision

Ship age									
1	**2**	**3**	**4**	**5**	**6**	**Collision**	**HRI**	**LRI**	**TRI**
/	/	/	/	/	/	20.3	9.0	5.5	7.25
100%	0	0	0	0	0	23.6			
0	100%	0	0	0	0	22.4			
0	0	100%	0	0	0	14.8			
0	0	0	100%	0	0	15.8			
0	0	0	0	100%	0	16.8			
0	0	0	0	0	100%	29.3			

Table 8 TRI of risk variables for all accident types

Node	**TRI**									
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**Average**
Ship age	7.25	10.38	2.59	2.58	2.45	3.64	2.59	3.03	5.44	4.44
Ship operation	11.45	7.10	0.94	0.88	4.45	1.75	1.06	4.91	6.09	4.29
Voyage segment	8.00	6.45	0.72	0.76	2.89	5.02	1.07	2.15	3.30	3.37
Vessel condition	5.75	0.01	0.09	1.54	2.17	1.26	2.77	1.29	1.70	1.84
Information	1.55	5.50	0.37	0.66	2.17	3.41	0.14	1.39	3.40	2.06

Specifically, in Table 7, the first row denotes the base-case scenario, and the following rows represent the different scenarios when each state of the variable reaches 100%. To obtain impact levels of such RIFs in accident types, TRIs are compared and ranked. Generally, the most important variables for ‘accident types’ are as follows:

Ship age > Ship operation > Voyage segment > Information> Vessel condition

In detail, the most important variables list for different accident types are demonstrated in Table 9.

Table 9 The most important variables

Accident type	**Ship age**	**Ship operation**	**Voyage segment**	**Vessel condition**	**Information**
S1 Collision	3	1	2	4	5
S2 Grounding	1	2	3	5	4
S3 Flooding	1	2	3	5	4
S4 Fire/explosion	1	3	4	2	5
S5 Capsize	3	1	2	4	4
S6 Contact/crush	2	4	1	5	3
S7 Sinking	2	4	3	1	5
S8 Overboard	2	1	3	5	4
S9 Others	2	1	3	5	4

From this point of view, different accident types are correlated with different variable priorities. For example, 'vessel condition' is the most important RIF for 'sinking', but the least important RIF for 'contact/crush'. 'Ship operation' contributes more to the accidents like 'collision', 'capsize', and 'overboard', than the accidents of 'sinking' and 'contact/crush'.

4.3.3 Model validation

To validate the model, it is examined by testing the combined effect of multiple RIFs to the accident types. Accounting for different states of the parent nodes, this study calculates the changed value of each state. The 'information' is selected as the first node, the state generating the highest changed value of state 1 (*i.e.* collision) in 'accident type' is increased by 10%, while the state generating the lowest changed value of state 1 in 'accident type' is decreased by 10%. This procedure is written as '~10%' in Table 10. Then, the same approach is applied to the next RIF, and the integrated changed value is obtained and updated. The updating procedure would continue until all RIF nodes are included. Similarly, the same updating procedure is applied into the state 2, 3… 9 in 'accident type' respectively, until all states are included.

The first column of the data in Table 10 shows the original values in TAN, and other columns state the updated changed values of results. However, each state of 'accident type' is calculated separately from each other, *i.e.* each row is computed through the change of states of RIFs in each accident type. From Table 10, the updated values of the target node are gradually increasing or decreasing along with the continuously changing RIFs, so that Axiom 2 is examined.

Table 10 Accident rate of minor change in variables

Information	**/**	**~10%**	**~10%**	**~10%**	**~10%**	**~10%**
Vessel condition	**/**	**/**	**~10%**	**~10%**	**~10%**	**~10%**
Voyage segment	**/**	**/**	**/**	**~10%**	**~10%**	**~10%**
Ship operation	**/**	**/**	**/**	**/**	**~10%**	**~10%**
Ship age	**/**	**/**	**/**	**/**	**/**	**~10%**

S1	20.3	20.4	21.2	21.5	22	22.2
S2	21.2	21.761	21.765	22	22.2	22.6
S3	3.69	3.72	3.74	3.76	3.79	3.8
S4	5.53	5.6	5.8	5.82	5.85	5.91
S5	11.1	11.3	11.6	11.7	11.8	11.9
S6	10.6	10.9	11.1	11.371	11.426	11.6
S7	4.15	4.16	4.52	4.57	4.61	4.68
S8	9.22	9.36	9.53	9.61	9.79	9.91
S9	14.3	14.6	14.86	14.945	15.1	15.3

Furthermore, the past maritime accidents (which were not included in the database used for the BN construction) are simulated in the proposed BN model to show the validation of proposed BN model. For instance, from the MAIB 5-2020, there was a collision between the bulk carrier Gülnak and the moored bulk carrier Cape Mathilde River Tees, in England on 18 April 2019. All the parameter settings for the proposed BN model can be obtained based on the descriptions, including

1) ‘Steel’ for hull type, ‘bulk carrier’ for ship type, ‘2011’ for the year of build, ‘179.88m’ for length, ‘23397’ for gross tonnage, ‘on passage’ for ship operation, ‘18 April 2019 0324 UTC+1’ for the time of day.

2) Vessel condition was good because ‘vessel had no deficiencies’ and ‘no evidence was found to indicate that Gülnak or any sister vessels had previously experienced unexpected difficulties when manoeuvring’.

3) Experience was good because of the qualified bridge team. Communication was good due to ‘the pilot and Gülnak’s master discussed the passage plan, …, advised that the vessel had no deficiencies and that its anchors were cleared away and ready for use’.

4) Sea condition and weather condition were both fine because of ‘the negligible tidal stream and the light winds’.

5) Equipment was not fully utilised. Although no direct cause was identified for the equipment malfunction, a recommendation had been made to ensure that the bridge equipment on the vessel is fully operational.

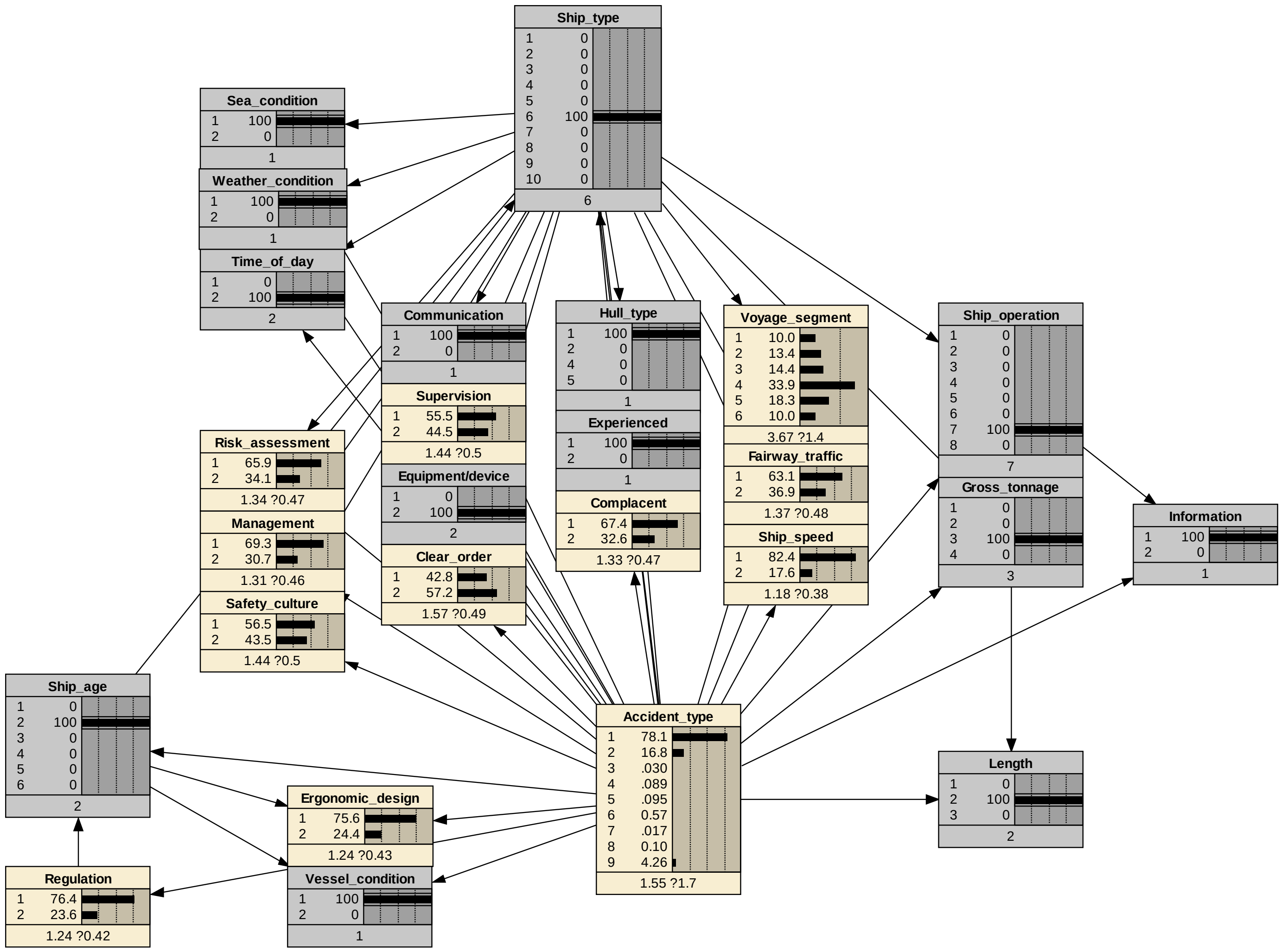

Fig.3 Model validation based on a past maritime accident

The accident report stated that the factors contributing to the inability to fully arrest Gülnak's turn were not apparent, and some information were not recorded. Therefore, the other nodes keep their generic original probabilities given no updated evidence is collected from the accident report. Based on the above parameter settings, it reveals a very high probability of 78.1% for the vessel to be involved in a collision, which further validates the proposed model, as shown in Figure 3.

4.4 Implications

The study enables the understanding of differences among critical factors, contributing to different types of accidents by incorporating human factors into the maritime accident analysis. The BN modelling can also help explain the most probable scenario with reference to a particular accident type.

To enable the MPE function, each variable will have a belief-bar at the 100% level, and usually some bars in RIFs are at lower levels, as seen in Fig. 4. It reveals the most probable configuration by assuming the state with the bar at the 100% level for each variable. The shorter bars indicate the relative low probabilities of the other states, given that the other variables are in the most probable configuration. In addition, they are scaled by the same factor used to bring the longest bar to 100%.

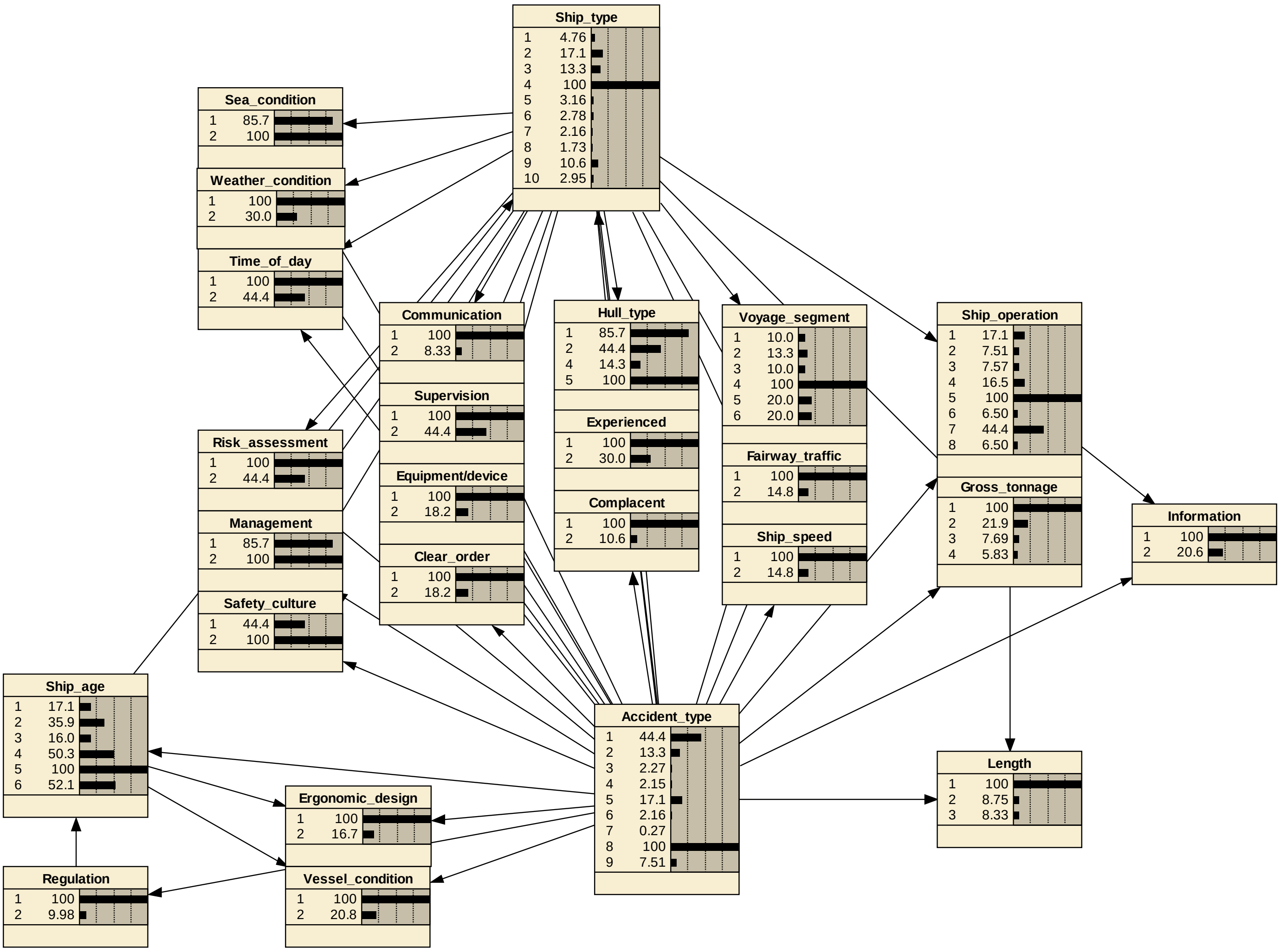

Fig. 4 Most Probable Explanation for BN model

From Fig. 4, ‘overboard’ is the most probable accident type, as its high occurrence frequency, and other RIFs reveal the corresponding most probable states. That is to say, a ‘fishing vessel’ tends to be ‘overboard’ within the following conditions:

1) Ship age ‘more than 20’, ship length ‘100m or less’, gross tonnage ‘300GT or less’, in ‘finishing’ operation and ‘mid-water’ voyage segment with ‘normal’ speed, in ‘good condition’, with friendly ergonomic design and correctly operating device, and with effective navigational information;

2) Bad sea condition, during the time from 7:00 to 19:00;

3) Dysfunctional management system, lack of safety culture.

With regards to this explanation, it emphasises the important causal relation between dysfunctional management system and overboard. The management system refers to shore management, maintenance management, bridge source management, on board management, port service, inadequate training, emergency drill, etc., which is a complex system as a significant variable influencing human factors for overboard. From the investigation of MAIB 24-2014, it is evident that the onboard management of Ovit (of which overboard of the fishing ship occurred), was dysfunctional, as well as the safety culture developed on the bridge was provided by the insufficient leadership of the master.

In addition, a lack of safety culture and precautionary thought are seen as the critical factors for human errors from Figure 4, which explains some dangerous behaviours of passengers or crews. Lu and Tsai (2008) conducted the factor analysis revealed six safety climate dimensions, and used logistic regression analysis to evaluate the effects of safety climate on vessel accidents. The results suggested the job safety has the most critical impact on vessel accidents, followed by management safety practices and safety training dimensions.

Similarly, when ‘accident type’ is selected as state 1 (collision), the MPE is displayed in Fig. 5.

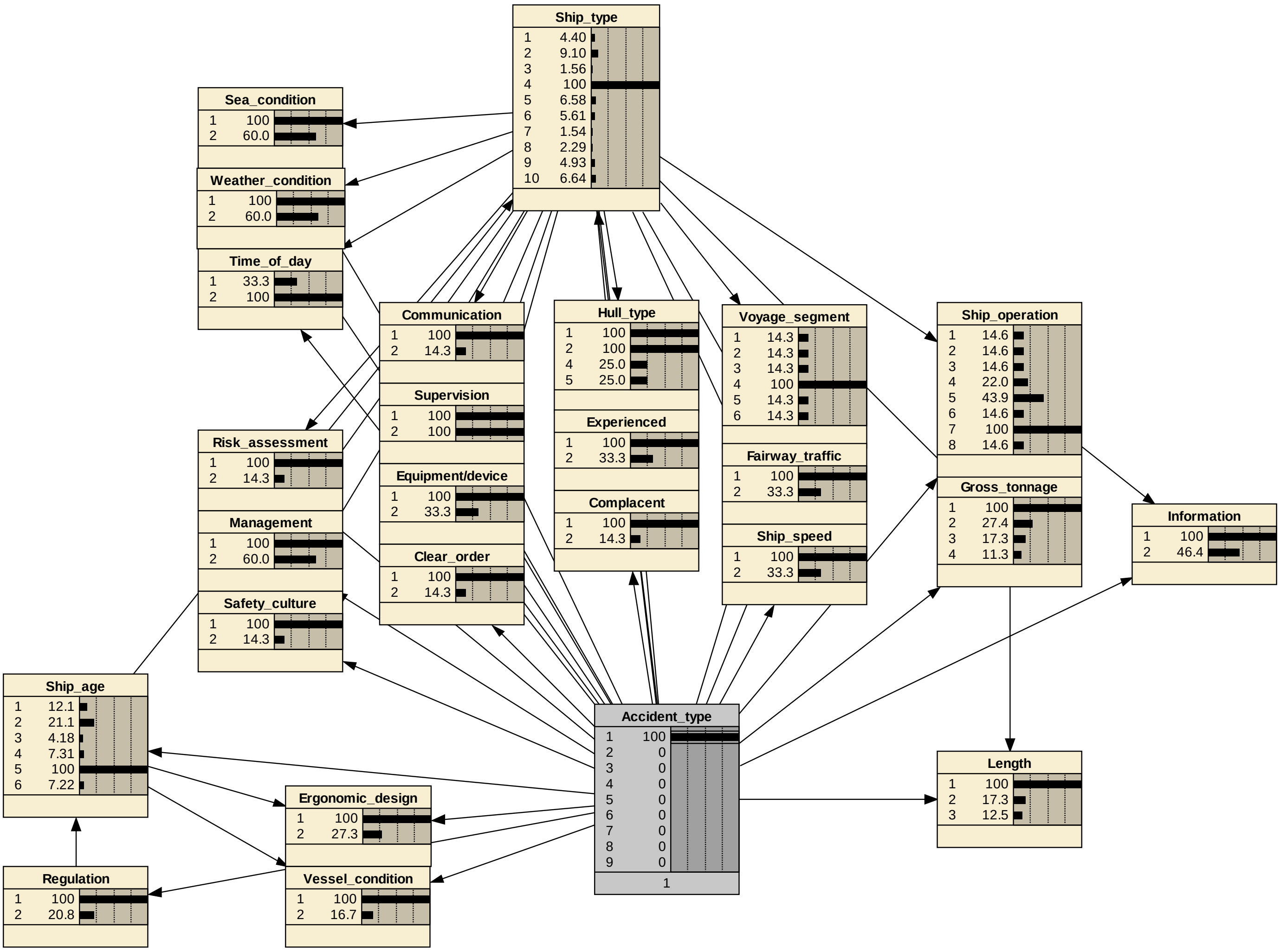

Fig. 5 Most Probable Explanation for ‘collision’

From Fig. 5, there are multiple 100% bars for 'hull type'. Normally, when two or more states of the same variable have bars that are at the 100% level, it indicates that there is more than one configuration with the highest probability (*i.e.* the configurations have equal probability). Then one of the states is to be entered with an artificial finding that the variable is in that state, to see how it changes the multiple 100% bars of other variables. When accident type is selected in Fig. 5, there is a high probability for the 'fishing vessel' to collide under these circumstances:

1) Ship age 'more than 20', ship length '100m or less', gross tonnage '300GT or less', 'on passage' operation and 'mid-water' voyage segment with 'normal' speed, in 'good vessel condition', with friendly ergonomic design and correctly operating device, and effective navigational information;

2) During the time before 7:00 or after 19:00;

3) Ineffective supervision or supports of operation.

Under this circumstance, ineffective supervision or supports of operation is strongly related to the collision in view of human factors. Ineffective supervision and supports, and improper supervision of loading operation are frequent during the navigation. Lone watchkeeper or working isolated makes the procedures onboard vulnerable to the hazards due to the workload pressure or onboard culture. From MAIB 17-2016 report, although required by the Arco Avon's SMS, the third engineer did not inform the chief engineer or the bridge officer of the leaking problem of fuel or his intention to fix it. The reason for him not doing so is probably to have been influenced by the onboard culture of routine working isolated and the absence of adequate and frequent communication. Also, Arco Avon's chief engineer's standing orders requiring the duty engineer to progress routine duties and conduct planned maintenance while on watch, effectively condoned working alone and disobeyed the guidance provided in the relevant safety regulations (e.g. the Code of Safe Working Practices for Merchant Seafarers 2015 edition). It all contributed to the mistakes the third engineer made. Moreover, from the MAIB 8-2014 report, the mater and chief officer kept lone watchkeeper on the bridge with the functional Bridge Navigational Watch Alarm System (BNWAS) switched off. According to this accident, and several similar others in the past, MAIB demonstrated that it was not safe for only two bridge watchkeepers to operate vessels because of the workloads placed on watchkeeping officers. Branch et al. (2004) reported that at least three of the fifteen ships which failed to keep a proper lookout at night to collision had lone watchkeepers on the bridge. Working isolated or improper supervision increases the risk of human errors in navigation compared to the situations where operations are under supervision.

By trying each of the possibilities, all the configurations that are at the highest probability level are revealed. Table 11 illustrates the MPE for all accident types. Although there are influences between different RIFs, poor vessel condition such as increasing complexity of propulsion arrangements or modification made to vessels size has a strong relation to sinking. Insufficient or lack of updated information, such as falsified records of information, relies on a single piece of navigational equipment, or without working indicators for necessary observing, contributes to grounding, contact, and other incidents. Ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion) is strongly related to fire and sinking. Also, it emphasises several human factor related variables under different accident types. For example, there is a high probability for collision to happen under the case of lone watchkeeper or working isolated. Grounding becomes probable under the circumstance with inadequate risk assessment, dysfunctional management system, unclear order from documents, and ineffective supervision. The most probable explanation given human factors for flooding is the lack of safety culture and precautionary thought. Human factors for capsize are related to lack of risk assessment, unclear order, and ineffective supervision. The situations with poor safety culture, dysfunctional management, and unclear order are strongly associated with sinking.

Table 11 Most Probable Explanation for all accident types

Variable	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
Ship age	5	5	5	5	1	6	5	5	2
Ship operation	7	1	5	7	1	7	1	5	2
Voyage segment	4	2	4	4	5	3	5	4	1
Vessel condition	1	1	1	1	1	1	2	1	1
Information	1	2	1	1	1	2	1	1	2
Ship type	4	3	4	4	2	7	2	4	9
Safety culture	1	1	2	1	1	1	2	2	1
Hull type	2	1	2	2	1	1	1	5	1
Gross tonnage	1	2	1	1	1	3	1	1	2
Regulation	1	1	1	1	1	1	1	1	1
Length	1	1	1	1	1	2	1	1	1
Ergonomic design	1	1	1	2	1	1	2	1	1
Sea condition	1	2	1	2	2	1	2	2	1
Risk assessment	1	2	1	1	2	1	1	1	2
Ship speed	1	1	1	1	1	2	1	1	1
Weather condition	1	2	2	2	1	1	1	1	1
Management	1	2	1	2	1	1	2	2	1
Clear order	1	2	1	2	2	2	2	1	2
Fairway traffic	1	1	1	1	1	1	1	1	1
Time of day	2	1	1	1	1	2	1	1	1
Complacent	1	1	1	1	1	1	1	1	1
Supervision	2	2	1	1	2	1	1	1	1

5. Conclusions

Compared to previous studies focusing on causal factors related to the severity and the probability of maritime accidents, this study uses a data-driven TAN approach, to investigate how different risk factors generate an impact on different types of maritime accidents with a focus on human factors. To identify RIFs, maritime accident reports from MAIB and TSB within a five-year period of 2012-2017, are extracted and reviewed to develop a primary database on maritime accidents. Then the risk-based TAN model is constructed to analyse RIFs incorporating human factors in maritime accidents. Lastly, the sensitivity analysis is conducted, as well as scenario analysis and MPE to implicate research contributions.

According to the calculations of the mutual information, crucial RIFs are ranked against different accident types. The results reveal that critical RIFs for maritime accident types are ‘ship age’, ‘ship operation’, ‘voyage segment’, ‘information’, and ‘vessel condition’. Meanwhile, it is evident that:

(1) The management system including shore management, maintenance management, bridge source management, on board management, port service, inadequate training, emergency drill, etc., is a significant variable influencing human factors for overboard. Besides, the lack of safety culture explains dangerous behaviours onboard, so as to cause overboard.

(2) Ineffective supervision is strongly related to collision. Working isolated or improper supervision increases the risk of human errors in navigation compared to operating under supervision.

(3) Collision tends to happen under the case of lone watchkeeper or working isolated. Grounding is probable under the circumstance with inadequate risk assessment, dysfunctional management system, unclear order from documents, and ineffective supervision. The most probable explanation on human factors for flooding is the lack of safety culture and precautionary thought. Human factors for capsize are related to lack of risk assessment, unclear order, and ineffective supervision. The situation with poor safety culture, dysfunctional management, and unclear order is strongly associated with sinking.

The scenario analysis provides a plausible explanation for the observed findings, revealing the most probable scenario concerning a particular accident type. Therefore, it can help identify the potential hazards and effectively assist maritime authorities in developing countermeasures for accident prevention.

Generally, the results from the TAN model present differentiation among the vital human factors contributing to different types of accidents, which helps provide useful insights for accident investigation and prevention. However, there is a drawback in the MPE method for implications. For instance, its results can change with the introduction of irrelevant variables, and be deceptive in the situations where even the most probable explanation is improbable.

Furthermore, there is a limitation on data representation. There were 161 reports involving 208 vessels (cases) in the study. The state 3 (flooding) of accident type accounts for 3.69% of all accidents, i.e. 7 cases of flooding. To present more representative results, more data to be continuously collected to support the model development. In future work, more attention will be paid to the variables, which are hard to measure in accident reports, *i.e.* mental workload, and situational awareness factors, to explore the risk analysis of individual factors on maritime accidents.

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